Artificial Neural Network Prediction of Aluminium Metal Matrix Composite with Silicon Carbide Particles Developed Using Stir Casting Method

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***Abstract*--** **Aluminium matrix composites (AMCs) are range of advanced engineering materials used for a wide range of applications. AMCs consist of a non-metallic reinforcement incorporated into Aluminium matrix providing advantageous properties over base metal alloys.**

In this paper, artificial neural network (ANN) is used to predict the micro-hardness, yield strength, tensile extension, modulus, ultimate tensile strength and stress, time to fracture, load at maximum extension, tenacity, electrical resistivity and conductivity. Information obtained from ANN model predictions can be used as guidelines during the conceptual design and optimisation of manufacturing processes; thus, reducing time and costs.

***Index Term*--** **Artificial Neural Network Aluminium Matrix Composites Modelling Mechanical Properties**

INTRODUCTION

Artificial Neural Network (ANN) is a class of parametric models that can accommodate a wider variety of nonlinear relationships between a set of predictors and a target variable. A neural network architecture is a promising implicit modeling scheme based on learning a set of parameters (weights), aimed at replacing the traditional explicit constitutive equations used to describe material behavior (Bezerra et al., 2010). ANN models can be solved using several software such as SAS Enterprise Miner (SAS v9.4) and MATLAB and even Microsoft Excel. SAS Enterprise Miner has two nodes that fit neural network models: the Neural Network node and the AutoNeural node (SAS Inc, 2014). The Neural Network node trains a specific neural network configuration; this node is best used when you know a lot about the structure of the model that you want to define. The AutoNeural node searches over several network configurations to find one that best describes the relationship in a data set and then trains that network. We shall be using MATLAB ANN Toolbox to solve our model. (Tiryaki, et al, 2014), in their study, an artificial neural network (ANN) model was developed for predicting an optimum bonding strength of heat treated woods using the MATLAB Neural Network Toolbox for the training and optimization of the ANN model.

ANN models have been applied to predict properties of AMCs produced by the Stir methods. (Altinkok and Koker, 2004), in their study, Al_2O_3/SiC particulate reinforced (aluminium matrix composites) AMCs, which was produced by using stir casting process, bending strength and hardening behaviour were obtained using a back-propagation neural network that uses gradient descent learning algorithm. They found that neural network was successful in the prediction of bending strength, hardness behaviour and also porous properties for any given SiC (μm) particles size range in the produced AMCs. An interesting study by (Boldsaikhan et al, 2011), introduces a novel real-time approach to detecting wormhole defects in friction stir welding in a nondestructive manner by evaluating feedback forces provided by the welding process using the discrete Fourier transform and a multilayer neural network. A one-hidden-layer neural network trained with the back propagation algorithm is used for classifying the frequency patterns of the feedback forces. They achieved, about 95% classification accuracy with no bad welds classified as good and hence demonstrates an approach for providing important feedback information about weld quality in real-time to a control system for friction stir welding.

With regards to wear properties of MMCs, several ANN models have been applied. (Hayajneh et al, 2009), in their work, predicted wear loss quantities of some aluminum–copper–silicon carbide composite materials, the results were firstly coded prior to training in a feed forward back propagation artificial neural network (ANN) and the results when compared with experimental results revealed the potential of ANN. (Rashed et al,2009), showed that, artificial neural network (ANN) approach was used to predict the wear behaviour of A356/SiC metal matrix composites (MMCs) prepared using rheocasting route. The ANN model was obtained to aid in prediction and optimization of the wear rates of the composites. Their results have shown that ANN is an effective tool in the prediction of the properties of MMCs, and quite useful instead of time-consuming experimental processes. (Jiang et al, 2008), applied artificial neural network technique to predict the mechanical and wear properties of short fiber reinforced polyamide (PA) composites using two experimental databases to train the neural network. The predicted property profiles as a function of short fiber content or testing conditions proved a remarkable capability of well-optimised neural networks for modeling concern.

ANN models have been applied in the prediction of mechanical properties of MMCs. Varol et al (2013), in their study, used artificial neural network (ANN) approach for the prediction of effect of physical and mechanical properties of Al2024–B_4C composites produced by powder metallurgy. By comparing the predicted values with the experimental data, they demonstrated that the well-trained feed forward back propagation ANN model is a powerful tool for prediction of effect of physical and mechanical properties of composites. Mukhopadhyay (2011), in his article elaborates the use of artificial neural networks (ANNs) in the prediction of static and dynamic mechanical properties, time-dependent properties like creep and stress relaxation, fatigue prediction, wear simulation, crack and damage detection of composites. Various recent developments and applications of ANNs, in the field of fibre reinforced composites have been discussed. Jalham (2003), showed the capability of the artificial neural network (ANN) to predict the effect of the hot deformation parameters on the strength of Al-base Metal Matrix Composites by comparing the results of the ANN predictions to the results of predictions by the Radial Basis Function (RBF) approach.

The use of ANN methods have been demonstrated by many researchers in estimating rather than measured with satisfactory results and hence reduce testing time and cost. (Hassan,et al, 2009), showed the potential of using feed forward back propagation neural network in prediction of some physical properties and hardness of aluminium–copper/silicon carbide composites synthesized by compocasting method using two input vectors. Density, porosity and hardness were the three outputs developed from the proposed network. Koker et al(2007) in their study, investigated the effect of four training algorithms, using a back-propagation neural network , on learning performance of the neural networks on the prediction of bending strength and hardness behaviour of particulate reinforced Al–Si–Mg metal matrix composites (MMCs). Al_2O_3/SiC particulates reinforced MMC was produced by using stir casting process. The work concluded that, Levenberg–Marquardt (LM) learning algorithm gave the best prediction for bending and harness behaviours of aluminium metal matrix composites.

Sha and Edwards (2007), noted the extensive use of artificial neural networks computer modeling techniques materials science and engineering research. They however, highlighted the growing tendency for the misapplication of neural network methodologies, limiting their potential benefit. Central to the problem is the use of over complicated networks that are frequently mathematically indeterminate, and by using limited data for training and testing.

METHODOLOGY

For prediction analysis of micro-hardness, yield strength, tensile extension, modulus, ultimate tensile strength, tensile stress, time at fracture (break), load at maximum extension, tenacity, electrical resistivity and conductivity, it was assumed that they are all functions of three parameters: percentage weight of aluminium (Wm), percentage weight of SiC (Wp) and size of SiC particle (Sp). Furthermore, all samples have similar geometric features and precautions were taken to make sure that the manufacturing and testing conditions were similar in all cases. The ANN model proposed for predicting the aforementioned mechanical and electrical properties of AlSiC composite is illustrated in Figure 1. It consists of a number of simple neuron-like processing elements, also called units or nodes, organized in layers that are classified as input layer, hidden layer(s), and output layer. These connections are not all equal; each connection has neurons with different weight and associated bias. These classifiers adjust internal parameters W performing vector mappings from the input to the output space Y(p) = AW(X(p)). In this way, the data were processed at the input layer and followed by network structure constituted by hidden layers until it arrives at the output layer. The input is a 3x17 matrix, representing 17 samples of 3 elements (see Table 2) and the output (target) is a 11x17 matrix, representing 17 samples of 11 elements (see Table 3).

About 70% of the data has been used in the training, and simulation steps and the rest of the data were used for validation and testing of the network model. The structure of the network can be represented as (3, HL1, HL2, 11), where HL1 and HL2 are the number of nodes in the first and second hidden layers, respectively. Each of the hidden layers has ten (10) nodes, hence the network topology (3,10,10,11), used the training data to learn the weights, and records the value of Mean Square Error (MSE). The Model equations are shown in Table I.

Table I
Model Equations

[redacted]						
1	Al/SiC/2.5p/0-45mm	%wt. at 2.5	Particle size	σ=-1.6602m^2+70.061m +736.63	H = 0.0843m + 20.64, R^2 =0.7143	σ_e=0.0013862m^2 - 0.093356m+69.456
2	Al/SiC/5.0p/0-45mm	%wt. at 5.0	Particle size	σ =-0.70001m^2+34.179 m+642.45	H = 0.239m + 21.19, R^2 =0.8249	σ_e=0.00058141m^2 - 0.15024m+68.133
3	Al/SiC/7.5p/0-45mm	%wt. at 7.5	Particle size	σ =-1.1501m^2+53.806m +809.33	H = 0.2914m + 22.528, R^2 =0.849	σ_e=0.0073248m^2 - 0.37581m+66.722
4	Al/SiC/10p/0-45mm	%wt. at 10	Particle size	σ=-0.84115m^2+39.97m +545.32	H = 0.3135m + 22.838, R^2 =0.8596	σ_e=0.010671m^2 - 0.63267m+59.546
5	Al/SiCp/0-10/3mm	Particle sizes, 3mm	%wt.	σ=-26.348w^2+310.57w +459.39	H = 0.692w + 19.32, R^2 =0.9396	σ_e = -1.908w + 73.473, R^2 =0.7366
6	Al/SiCp/0-10/9mm	Particle sizes, 9mm	%wt.	σ=-20.971w^2+230.46w +521.04	H = 0.652w + 20.63, R^2 =0.8896	σ_e = -2.0238w + 72.088, R^2 =0.9213
7	Al/SiC/0-10/29mm	Particle sizes, 29mm	%wt.	σ=-19.58w^2+246.53w+ 486.04	H = 1.576w + 19.37, R^2 =0.933	σ_e = -1.2244w + 71.671, R^2 =0.8278
8	Al/SiC/0-10/45mm	Particle sizes, 45mm	%wt.	σ=-11.504w^2+148.65w +359.56	H = 1.64w + 20.95, R^2 =0.8637	σ_e = -1.7725w + 71.535, R^2 =0.8204

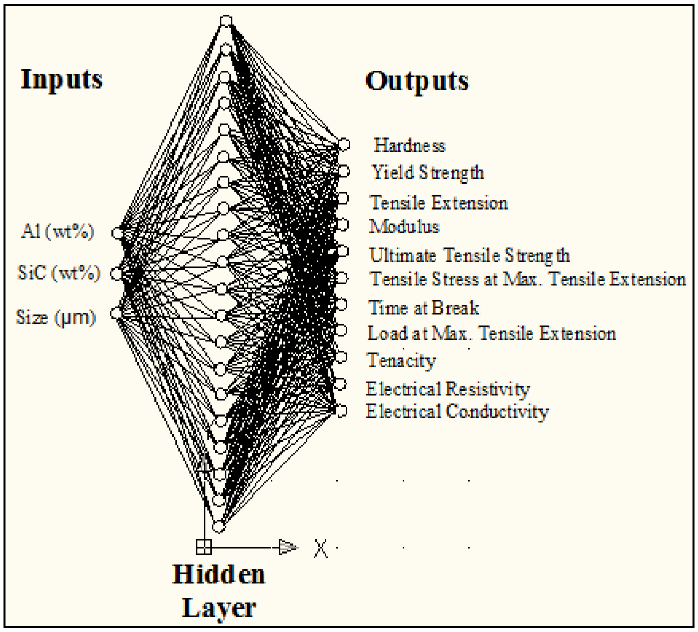

Fig. 1. The ANN Architecture

Table II
ANN Input Data

1	100	0	0
2	97.5	2.5	3.00E-06
3	95	5	3.00E-06
4	92.5	7.5	3.00E-06
5	90	10	3.00E-06
6	97.5	2.5	9.00E-06
7	95	5	9.00E-06
8	92.5	7.5	9.00E-06
9	90	10	9.00E-06
10	97.5	2.5	2.90E-05
11	95	5	2.90E-05
12	92.5	7.5	2.90E-05
13	90	10	2.90E-05
14	97.5	2.5	4.50E-05
15	95	5	4.50E-05
16	92.5	7.5	4.50E-05
17	90	10	4.50E-05

Table III
ANN Output (Target) Data

N/S	Maximum Tensile Extension (mm)	Maximum Tensile Extension (N)	Modulus (N/mm^2	Yield Strength (MPa)	Tensile Strength (MPa)	Fracture (gf/tex)	Time at Fracture (Standard) (sec)	**Hardness (HV)**	**Conductivity, σ(Mς/m)**	**Resistivity, ⚘(μΩ-m)**	Tensile Extension (MPa)
1	20.783118	720.0062	402.413324	40.8	61.3	845.6629	40.8032	19.6	70.25378	**0.014234**	15.175522
2	10.685998	353.2760581	1293.428876	29.6	37.2	381.4674	21.3124	**20.05**	68.82136	**0.01453**	8.160014
3	10.84656	419.33323	1028.563265	35	53	438.4278	21.65	23.6	67.70123	**0.014771**	9.35811
4	7.945935	314.2605334	1517.59211	24.25	31.625	320.9439	15.883	24.75	64.14723	**0.015589**	6.76695
5	8.6769125	420.8433258	878.9286575	22.25	28.25	434.3051	17.3	25.9	48.74027	**0.020517**	5.649625
6	8.14303	688.626658	1290.11912	30.4	40	711.551	16.22	22.95	67.83901	**0.014741**	13.039944
7	7.156814	374.4512296	888.772108	16.8	24	383.5274	14.3	24.65	62.96254	**0.015882**	6.403696
8	7.01875	498.46985	1092.8752	21.625	26.5	519.2085	13.975	26.05	59.82686	**0.016715**	10.044365
9	6.4023433	291.1302844	760.3567167	11.667	13.867	301.7488	12.73333	26.2	48.96254	**0.020424**	4.4393267
10	11.061328	698.093155	1233.86522	30.75	41.625	721.5803	22.075	23.55	68.63504	**0.01457**	13.083903
11	9.46796	688.299396	969.405182	36	47.6	746.2332	18.7772	25.2	66.96015	**0.014934**	14.489662
12	6.3033333	62.09007	1326.21316	31.667	39.667	63.55679	12.57733	33.65	65.26178	**0.015323**	1.14747
13	13.491654	615.047286	990.415216	28	42.1	756.6384	46.5948	34.25	56.63504	**0.017657**	12.173872
14	12.404812	503.244	580.916218	22.8	33.46	610.1167	14.2568	23.85	67.80000	**0.014749**	8.624638
15	12.6141	453.2824975	793.2229175	34.5	44.75	497.3207	15.1	33.45	61.58468	**0.016238**	9.3490325
16	6.746216	762.192954	935.028496	19.8	27.62	780.5672	40.42	33.65	63.45271	**0.01576**	13.021274
17	10.785468	382.0129175	645.46291	29.125	39.625	398.2237	21.52	35.2	50.27102	**0.019892**	6.3503725

A data set of measured results will usually be divided into three data sets: training, testing, and validation of the neural network. The training data set is used to adjust the weights of all the connecting nodes until the desired error level is reached. The ANN performance can be evaluated using the coefficient of determination *B* (also called R^2 coefficient), which is defined by:

$$B = 1 - \frac{\sum_{i=1}^{M}(O(p^{(i)}) - O^{(i)})^2}{\sum_{i=1}^{M}(O^{(i)} - O)^2}$$

where $O(p^{(i)})$ is the *i*th predicted property characteristic, $O^{(i)}$ is the *i*th measured value, *O* is the mean value of $O^{(i)}$, and *M* is the number of test data. The coefficient *B* describes the fitness of the ANN output variable approximation curve to the actual test data output variable curve. Higher *B* coefficients indicate an ANN with better output approximation capabilities. To avoid any influence in selecting the test data, a random technique was applied in the selection, and the entire process is repeated independently many times. Afterward, the distribution of *B* values is recorded and the percentage of $B \geq 0.9$ is calculated, since this value is identified as corresponding to a high predictive quality, that is, less than 15% of the root mean square error is between the predicted values and the measured ones. It is clear that the higher the percentage of *B* ($B \geq 0.9$), the better the quality (Bezerra et al., 2010). Another aspect that should be observed is the increase of the percentage of test data with a *B* value of ≥0.9 as a function of the number of neurons in the hidden layers.

RESULT AND DISCUSSIONS

In this section, results are discussed using the network (Figure 1) to predict the microhardness, yield strength, tensile extension, modulus, ultimate tensile strength, tensile stress, time at fracture (break), load at maximum extension, tenacity, electrical resistivity and conductivity. The maximum performance was reached using a multilayer perceptron composed by 20 neurons in two hidden layers.

The regression R values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship and from Figure 4, Training has R value of 0.99987, Validation has R value of 0.92398, Test has R value of 0.9448 and All has R value of 0.96826. It can be inferred that there is close relationship between the outputs and the targets.

Training samples were presented to the network during training and the network was adjusted according to its error, **Validation** samples were used to measure network generalization and to halt training when generation stops improving, while **Testing** samples have no effect on training and so provided an independent measure of network performance during and after training (Figure 2 and Figure 3). The summary of ANN results, a pattern recognizing tool is indicated in Figure 4.

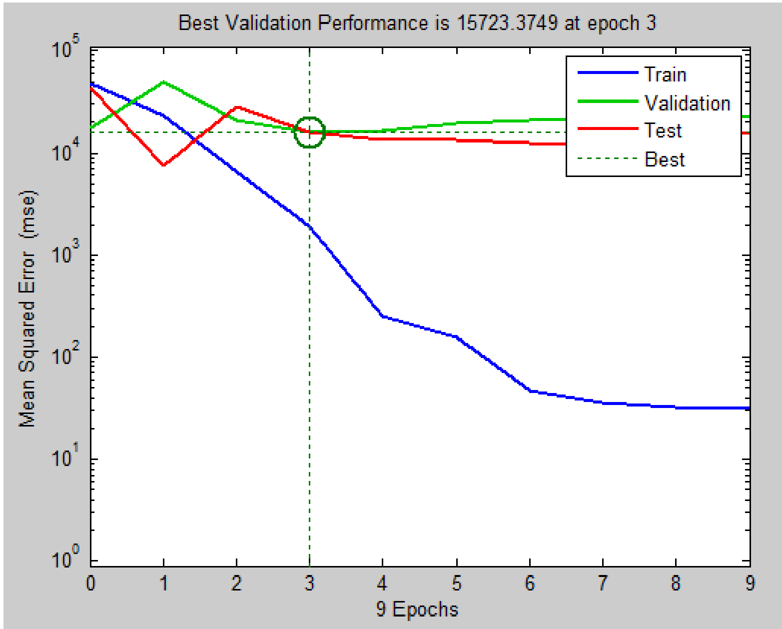

Fig. 2. ANN Training Graph for the Data Used.

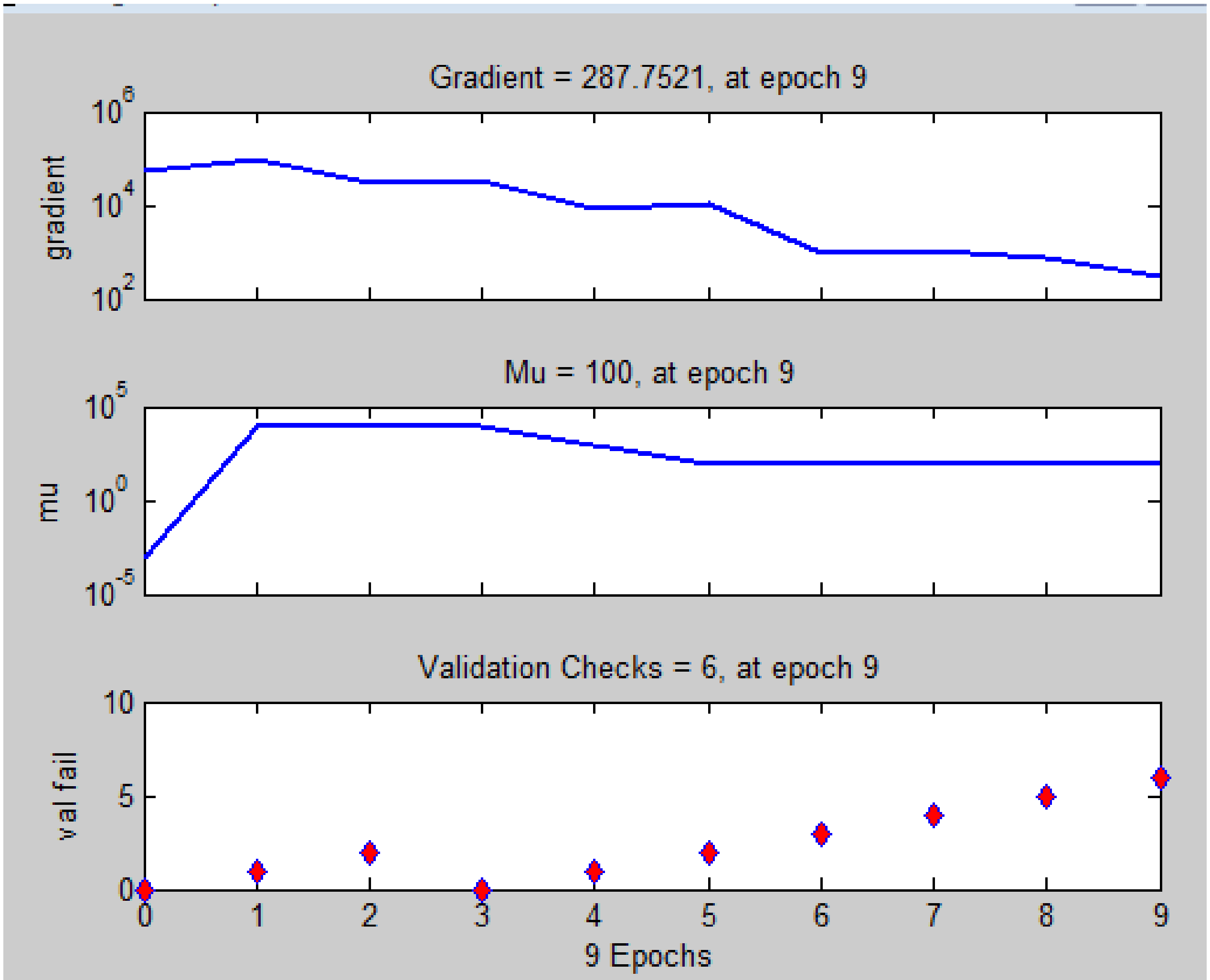

Fig. 3. The ANN Validation Checks, Mu and Gradient

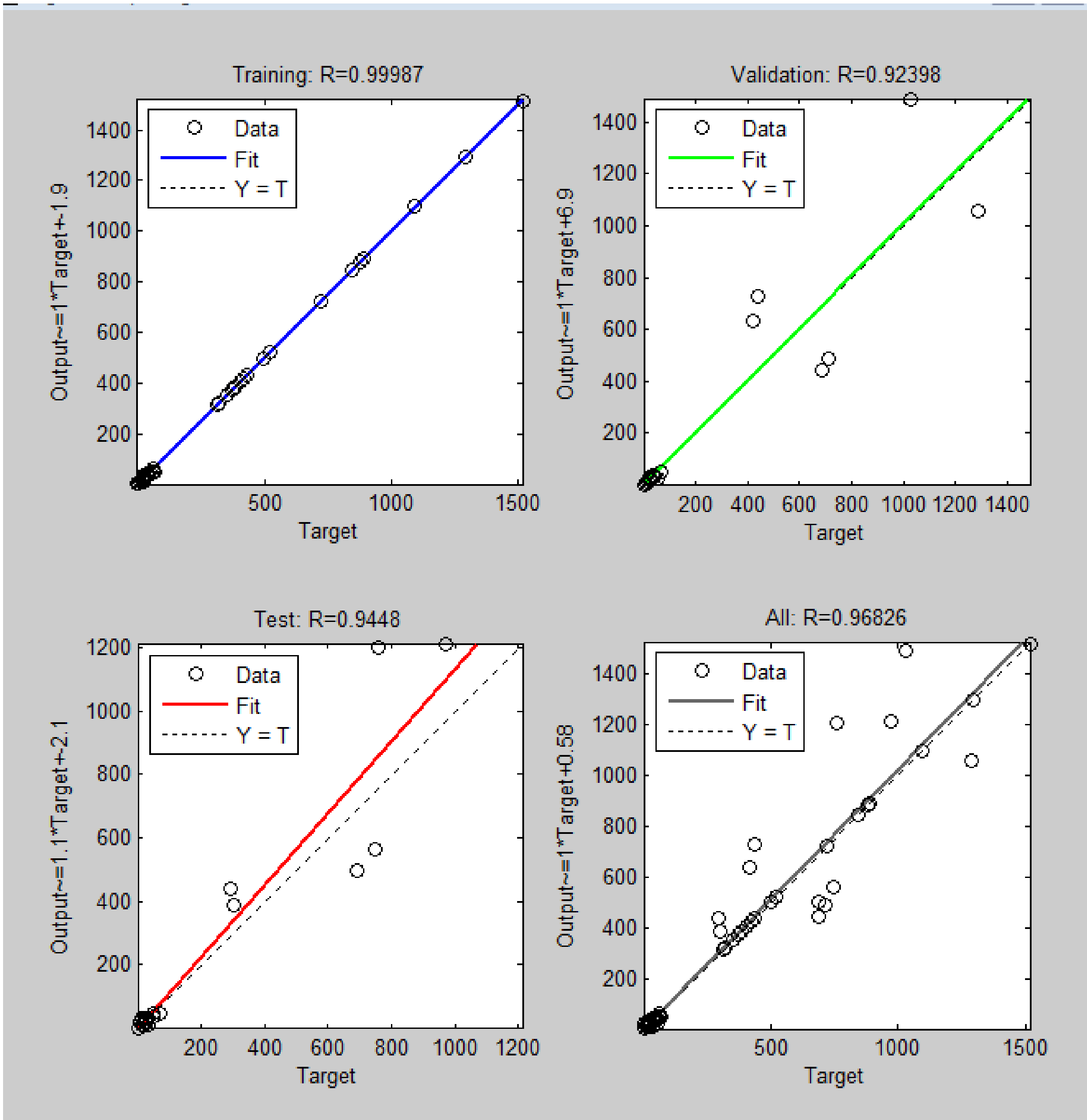

Fig. 4. ANN Output Graph for the Dataset.

Conclusions

The hardness of the composite was found to be considerably higher than that of the matrix alloy and increased with increasing particle content. The higher hardness of the composite samples relative to that of the matrix Al-alloy could be attributed to the reducing grain size and existing of nano-hard particles acting as obstacles to the motion of dislocation. The addition of ceramic particles resulted in significant improvements in yield strength and ultimate tensile strength of the composites. Different strengthening mechanisms contributed in the obtained strength improvements including Orowan strengthening, grain refinement, and the load bearing effects.

Unlike the experimental approach, which is time consuming, the use of Excel, MATLAB and ANN method are capable of generalizing the complex relationships and provide approximate solutions. Mechanical properties are related to volume percentage and the size of SiC in the composite. Information obtained from the model predictions and simulations can be used as guidelines during the conceptual design and optimization of manufacturing processes; thus, reducing the time and costs that would otherwise be incurred by experimental methods.

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